Business Failure Prediction: A Study of Indian Companies

Final synopsis of the Ph.D. thesis submitted to Mangalore University for the award of the degree of

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1. Introduction

Business failure, often referred to as corporate insolvency or bankruptcy, is a critical concern for investors, creditors, and regulatory bodies because of its significant impact on the economy and stakeholders. The prediction of business failure is essential for mitigating financial risk and ensuring firm stability. Various models and techniques have been developed to predict corporate failure, including financial ratio analysis, discriminant analysis, and hazard models (Beaver, 1966; Shumway, 2001).

Predicting business failure is similar to solving complex equations, with far-reaching consequences across the complex field of corporate management. Business failure, marked by a firm's inability to meet its obligations and continue operations, is not merely an endpoint but a phenomenon with profound strategic, economic, and social implications. This represents a juncture where financial distress, operational inefficiencies, and external adversities converge, culminating in corporate insolvency, restructuring, and liquidation. Understanding and predicting such failures have been an essential area of focus for researchers, policy analysts, and practitioners, given their significant consequences for shareholders, creditors, employees, and the broader economy.

Common causes of failure include low profitability, inappropriate diversification, import penetration, deteriorating financial structures, and operational challenges. Younger companies are generally considered riskier because of their limited history and resources (Blum, 1974).

2. Conceptual Background

Business failure, also known as corporate failure, refers to the termination of a firm's operations due to its inability to generate adequate revenue to cover expenses or meet financial obligations. It is a complex process, frequently preceded by a period of financial hardship, characterized by declining profitability, diminishing market share, and escalating debt. Comprehending the conceptual framework of business failure is paramount for developing effective prediction models, particularly within the context of Indian companies.

Various factors can lead to business failure, which can be broadly classified as internal and external. Internal factors pertain to the firm's management, operations, and financial decisions, such as poor strategic planning, inadequate financial controls, inefficient operations, lack of innovation, or ineffective leadership. Conversely, external factors are beyond the firm's direct control and encompass macroeconomic conditions, industry competition, regulatory changes, technological disruptions, and even natural disasters.

Bankruptcy or business failure is a multidimensional concept that encompasses the termination of a firm's operations due to its inability to generate sufficient revenue to cover expenses or meet financial obligations (Dimitras et al., 1996). It is a complex process that is often preceded by a period of financial distress characterized by declining profitability, diminishing market share, and escalating debt levels.

Bankruptcy is consistently defined across multiple studies as a legal process that occurs when a company is unable to meet its debt obligations, often leading to the reorganization or liquidation of its assets. This state of financial distress is considered the final stage of business failure, where a firm is legally declared unable to pay its debts (Abidali & Harris, 1995; Antunes et al., 2017; Casey, 1980; Christidis & Gregory, 2010; Dimitras et al., 1999; Houghton & Woodliff, 1987; Li, 2012; Li et al., 2010; Sami, 2016)

3. Significance of Business Failure Prediction

Predicting and preventing business failures is of paramount importance to various stakeholders, including investors, creditors, regulators, and managers. Accurate forecasting models empower these stakeholders to identify companies facing bankruptcy risks, enabling timely interventions to mitigate losses and potentially avert complete collapse. For investors, reliable predictions can inform investment decisions and help avoid potential financial pitfalls. Creditors can leverage these models to assess borrowers' creditworthiness and manage their risk exposure more effectively. Regulators can utilize prediction models to detect systemic risks and implement appropriate policies to maintain financial stability. From the managers' perspective, understanding the factors contributing to business failures can inform strategic decision-making and enhance the long-term viability of their companies. Hence,

research in business failure prediction is crucial for cultivating a more stable and resilient business environment.

3.1 Legal Perspective of Business Failure in India

The legal framework governing business failure in India is predominantly shaped by the Insolvency and Bankruptcy Code, enacted in 2016. This legislation marks a significant overhaul of the previous insolvency laws, aiming to streamline the insolvency resolution process and maximize the value of assets for stakeholders. The IBC establishes a structured, time-bound procedure for resolving insolvency, fostering transparency and efficiency in addressing distressed companies.

4. Literature Review

Defining business failure precisely is interesting because of its multifaceted nature and varying interpretations across different contexts. Theoretical and operational definitions are essential for a comprehensive understanding.

Theoretically, business failure encompasses a range of situations in which a firm ceases operation because of its inability to achieve its economic objectives or meet its financial obligations. This broad definition covers various scenarios, including

Insolvency: A state in which a company's liabilities surpass its assets, rendering it unable to meet its current debt obligations (Anjum, 2012).

Bankruptcy: A legal process initiated by a court order, often triggered by insolvency, where a company's assets are liquidated to repay creditors (Sidhu & Katoch, 2019).

Business failure: A bigger term that includes both insolvency and bankruptcy, as well as other situations in which a firm is unable to sustain its operations and achieve its strategic goal (Arasti, 2011).

4.1 Review based on Financial Ratios

Several seminal studies have shaped the landscape of business failure prediction, pioneered the use of financial ratios as predictors and demonstrated their ability to discriminate between failing and non-failing firms (Beaver, 1966). Research solidified this approach by introducing the Z-score model, a multivariate statistical model that uses financial ratios to assess bankruptcy risk (Altman, 1968). builds upon this

foundation, refining the statistical methodology and highlighting the importance of considering the timing of financial information (Ohlson, 1980).

4.2 Non-Financial Determinants

While financial determinants provide quantifiable measures of a company's financial health, non-financial factors also play a significant role in predicting business failure. These factors are often more qualitative and can be interesting to measure but offer valuable insights into a company's resilience and long-term sustainability. An effective board of directors provides oversight and strategic guidance for management. A diverse and independent board can enhance decision-making and reduce the risk of mismanagement (McCann and Vroom, 2013). Effective leadership and management are crucial for navigating challenges and ensuring a company's long-term success. Experienced and competent leaders can develop and execute sound business strategies, motivate employees, and adapt to changing market conditions (Danilov, 2014).

4.3 Review Based on Macroeconomic Variables

Several studies have examined the influence of macroeconomic conditions on the financial performance and likelihood of business failure (Acosta-González et al., 2017; Anghel et al., 2020; Baharin et al., 2020; Bansal & Singu, 2023; DiPietro & Sawhney, 1977; D'Souza & Chandrashekhar, 2024; Fernández-Gámez et al., 2019; Mare, 2015; Perboli & Arabnezhad, 2021; Sehgal et al., 2021; Tinoco & Wilson, 2013; Žiković, 2016) findings suggest that macroeconomic variables, particularly GDP growth and interest rates, are significant predictors of business failure, highlighting the need to consider the broader economic environment when assessing the financial health of organizations.

4.4 Review of Studies Based on Intelligent Techniques

Random Forest is a robust ensemble learning algorithm that has demonstrated its effectiveness in the domain of business failure prediction (Narvekar & Guha, 2021). Artificial Neural Networks in bankruptcy prediction, highlighting their application alongside other techniques like statistical methods, decision trees, and support vector machines. (Kováčová & Klieštiková, 2017). Recent studies demonstrated the superior performance of a generalized regression neural network, which outperformed other machine learning models in predicting corporate bankruptcy with an accuracy of

99.96%. (Pereira et al., 2014 ; Lahmiri & Bekiros, 2019 ; Mancisidor, 2022). A hybrid model combining data depths and nonlinear Support Vector Machines improves corporate bankruptcy prediction. Empirical results using Korean manufacturing firm data show higher accuracy compared to existing methods, offering valuable guidance for investors. The appeal of ensemble methods lies in their ability to leverage the strengths of individual models while mitigating their weaknesses. Ensemble methods combine multiple models to improve overall predictive performance by leveraging the strengths of individual models (Wang & Wu, 2017).

4.6 Review of Indian studies on business failure prediction

The body of literature on business failure prediction in the Indian context, while not as extensive as in other countries, has produced several noteworthy studies that offer valuable insights. A study combined both financial and non-financial variables in their model to predict corporate financial distress in India. The authors find that institutional shareholding, a non-financial variable, is strongly associated with financial distress, contrary to the findings of many earlier studies (Balasubramanian et al., 2019).The bankruptcy prediction models for Indian manufacturing companies. Using multiple discriminant analysis and logistic regression on a dataset of 208 companies (104 bankrupt and 104 non-bankrupt), they re-estimated Altman's Z-score, Ohlson's O-score, and Zmijewski's X-score. They found that the re-estimated models performed better and proposed a new model with higher accuracy. Addressing the gap in outdated models, they contribute to an improved bankruptcy prediction model tailored to the Indian manufacturing sector (Singh & Mishra, 2016). Altman’s Z-score model for Indian auto and auto ancillary companies listed on the NSE Small Cap and Mid Cap indices. Using 12 years of financial data (2000-01 to 2011-12) from 10 companies, they assessed the model's predictive power. This study finds that Altman's model is inaccurate for classifying these companies, highlighting its limitations in the Indian context. Addressing the gap in sector-specific applications, they contribute to an empirical evaluation of a widely used model, suggesting the need for further research and model refinement for the Indian auto industry (Vijayakumar & Rajendra 2015).

5. Overview of Business Failure Prediction Models

5.1 Altman's Multivariate Model: Edward Altman's Z-score, introduced in 1968, marked a significant advancement in bankruptcy prediction by employing a multivariate approach. Unlike earlier univariate analyses that examined ratios in isolation, Altman combined five key financial ratios, reflecting different facets of a company's financial health: liquidity, profitability, leverage, solvency, and operational efficiency.

5.2 Ohlson's Probabilistic Model

James Ohlson's O-score model, developed in 1980, employed a probabilistic approach to predict the likelihood of a firm's bankruptcy. O-score model incorporates a broader range of financial indicators than previous models, including not only traditional ratios but also key accounting variables such as cash flows, earnings, and book values (Ohlson, 1980). This comprehensive approach allows the model to capture a more complete picture of a company's financial health. The O-score was calculated using a logistic regression model, which outputs a probability score between 0 and 1, with a higher score indicating a greater likelihood of financial distress (Ashraf et al., 2019).

5.3 Zmijewski's Probit Model

Zmijewski proposed a refined statistical model for predicting bankruptcy using a probit analysis approach. This differs from earlier models, such as Altman's Z-score, which employed discriminant analysis. Zmijewski's model leverages the probit method to estimate bankruptcy probability based on a carefully selected set of financial ratios, focusing on profitability, leverage, and liquidity. These ratios were chosen because of their demonstrated performances in previous studies. (Kováčová & Klieštiková, 2017).

5.4 Taffler's Model

Taffler's 1983 model is notable for its holistic approach to predicting insolvency. (Giacosa et al., 2015). Instead of solely relying on a limited set of financial ratios, Taffler's model incorporated a broad range of factors, encompassing capital adequacy, liquidity, leverage, profitability, and other key aspects of a company's financial well-being. His research involved a large-scale examination of both financially stable and

distressed firms, analyzing a selection of 80 financial ratios to identify the most salient predictors. Through the application of statistical techniques, including multivariate discriminant analysis, Taffler developed a model that considers multiple dimensions of a company's financial performance.

5.5 Springate's Model

Gordon L.V. Springate, a researcher at Simon Fraser University, developed a bankruptcy prediction model in 1978 that was built upon Altman's multivariate discriminant analysis framework. Springate's model was explicitly tailored to Canadian companies by applying the MDA technique to a sample of 40 Canadian firms. This study revealed that Springate's model achieved an impressive accuracy rate of 92.5% when used to assess the financial health of Canadian businesses. Notably, the model exhibited the lowest Type I error rate compared with other distress prediction models in the Canadian context, indicating its strong capability to correctly identify financially distressed companies.

6. Statement of Problem

This study addresses the critical problem of accurately predicting business failure in Indian companies. The lack of reliable prediction models tailored to the Indian business environment poses significant risks to various stakeholders. Without effective early warning systems, companies may miss opportunities to implement corrective measures, leading to increased financial distress and a potential collapse. Lenders and investors face greater uncertainty in assessing credit risk and making investment decisions, potentially resulting in substantial financial loss. Policymakers may struggle to design effective interventions to support struggling industries, thereby hindering their economic stability and growth. Moreover, employees may face unexpected job losses without adequate time to prepare and seek alternative employment. This study aimed to mitigate these risks and enhance the resilience of the Indian business landscape by developing a robust and context-specific prediction model.

7. Research Gap

The existing literature on business failure prediction models has been dominated by studies conducted in developed economies, particularly the United States and Europe. While these models provide a useful starting point, the Indian corporate environment is distinct, with its own cultural, regulatory, and economic factors that can impact a company's financial well-being and risk of insolvency.

There is a lack of comprehensive comparisons of the performance of different business failure prediction models, including hybrid and AI-based approaches, in the Indian context. Limited research has been conducted on integrating financial and macroeconomic data to develop holistic and accurate prediction models. Emphasizing the necessity for context-tailored approaches to predict business failures, which account for the distinctive features of the Indian business landscape.

8. Research Questions

This study seeks to address the following research questions:

1. What are the key financial, nonfinancial, and macroeconomic factors that contribute to business failure in Indian companies?
2. How well do traditional business failure prediction models perform in the Indian corporate context?
3. How do traditional business failure models compare with machine-learning-based models in terms of predictive accuracy?
4. Can an integrated new prediction model combining financial, non-financial, and macroeconomic variables improve business failure prediction?
5. How does the predictive performance of machine learning models vary across different time horizons?

9. Research Objectives

1. To identify the key financial, non-financial, and macroeconomic determinants of business failure among Indian companies.
2. To apply traditional prediction models to Indian companies and evaluate their predictive accuracy.

3. To compare the prediction accuracy of traditional models with that of machine learning models.
4. Develop a comprehensive business failure prediction model incorporating financial, non-financial, and macroeconomic factors relevant to the Indian business environment.
5. To assess the advanced predictive accuracy of machine learning models across different time horizons.

10. Research Design and Methodology

This study employs a combination of statistical and artificial intelligence techniques to develop a business failure-prediction model. The study used logistic regression, decision trees, and neural networks to analyse the association between predictor variables and the likelihood of business failure (Pereira et al., 2014; Bhandari & Iyer, 2013).

The study follows the below methodology:

1. Situation Analysis: Identifying the Problems and Opportunity for Research.
2. Conceptual Endowment: Identifying the Gap from the Literature.
3. Methodology: Research Design, Approach, Strategies, Tools, Techniques and Methods.
4. Data Collection: financial and non-financial data for selected Indian companies.
5. Data Pre-processing: Clean and prepare the data for analysis, including handling missing values and outliers.
6. Feature Selection: Identify the most relevant financial, non-financial, and macroeconomic variables that contribute to business failure prediction.
7. Model Development: Train and develop business failure prediction models using selected Machine Learning procedures.
8. Model Evaluation: Assess the predictive performance of the developed models using appropriate metrics, such as accuracy, precision, recall, and F1-score.
9. Comparative Analysis: Compare the performance of traditional statistical and artificial intelligence-based models to determine the most effective approach for predicting business failures in the Indian context.

11. Data Selection

The dataset comprises financial and non-financial data on publicly listed Indian companies for the period 2007–2023. The sample includes both failed and non-failed companies, with failure defined as filing for bankruptcy, liquidation, or delisting from a stock exchange. The data are sourced from Prowess CIME, Moneycontrol, Trendlyne, BSE, and NSE for financial and non-financial data and the RBI, World Bank, and IMF database for macroeconomic data.

This study focuses on publicly listed companies on the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE), encompassing a diverse range of sectors. This study provides a longitudinal perspective on business failure predictions in India. Initially, the data set was 177 companies, but due to the no availability of data, the study incorporated the sample of 140 Indian listed firms, consisting of 70 failed companies and 70 non-failed companies from the BSE Midcap segment, providing a balanced representation of successful and unsuccessful businesses. This balanced approach allows for a comparative analysis of the factors that contribute to business failure and success in the Indian context. The inclusion criteria for failed companies are delisting from the stock exchange due to financial distress, entering liquidation proceedings, or filing for bankruptcy. Non-failed companies are those that have maintained a continuous listing on the BSE/NSE throughout the study period and have not experienced any of the aforementioned failure events. This selection process aimed to ensure a clear distinction between the two groups and enhance the validity of the comparative analysis.

12. Limitations of the Study

1. No availability of all financial data of failed companies.
2. The sample size chosen for the study is limited.
3. External factors, such as global economic crises, may have an impact on financial distress, but they have not been completely accounted for.
4. Although machine learning algorithms outperform traditional models, their efficacy varies by industry and geographic area.
5. Overfitting Concerns in some models, particularly Neural Networks and Decision Trees, result in poor generalization performance in testing.

6. The dataset focuses exclusively on Indian companies, limiting the applicability of the findings to other economies and industries. Business failure patterns may vary depending on market conditions, regulations, and industry-specific financial structures.

Notwithstanding these constraints, this study seeks to offer significant insights into the prediction of business failure in India, thereby enriching both academic literature and practical decision-making for many stakeholders within the Indian corporate environment.

13. Research Hypothesis

Based on the literature review and research objectives, the following hypotheses were tested:

Null Hypothesis (H_0): Financial variables do not differ significantly between failed and non-failed companies.

Alternative Hypothesis (H_1): Financial variables differ significantly between failed and non-failed companies.

Null Hypothesis (H_0): There is no significant difference in the predictive accuracy among existing business failure models.

Alternative Hypothesis (H_1): There is a significant difference in the predictive accuracy among existing business failure models.

Null Hypothesis (H_0): There is no significant difference in the predictive accuracy among the Machine Learning models**.**

Alternative Hypothesis (H_1): There is a significant difference in the predictive accuracy among the Machine Learning models.

Null Hypothesis (H_0): Traditional business failure prediction models do not significantly differ in prediction accuracy from machine learning models.

Alternative Hypothesis (H_1): Traditional business failure prediction models differ significantly in prediction accuracy compared to machine learning models.

Null Hypothesis (H_0): The predictive accuracy of Machine Learning models does not exhibit substantial variation when predicting business failure at different time horizons.

Alternative Hypothesis (H_1): The predictive accuracy of Machine Learning models exhibits substantial variation when predicting business failure at different time horizons.

14. Tools used for data analysis

The analysis is facilitated by a combination of tools, including MS Excel for data handling, Python codes used in Google Colab for developing machine learning model execution, JASP and Statisty for statistical analysis, and Regressit for regression analysis and modeling.

15. Data Analysis and Interpretation

15.1 Descriptive statistics

To identify key financial, non-financial, and macroeconomic factors related to business failure in Indian companies and compare the impact of variables between failed and non-failed companies. Descriptive statistics, such as minimum, maximum, mean, standard deviation, and coefficient of variation, were used to understand the characteristics and distribution of the data.

Non-failed companies' financial stability, profitability, liquidity, leverage, efficiency, and macroeconomic resilience can be gleaned from their descriptive study. The fact that profitability ratios like Return on Assets (ROA) and Net Income to Total Assets (NI/TA) have positive mean values (0.09 and 0.10, respectively) shows that these businesses successfully make money on their assets. Most industries maintain steady returns, but a small number of outliers exhibit extraordinarily high performance or volatility in profitability according to the significant skewness in Return on Equity (ROE) and Return on Capital Employed (ROCE).

Significant financial instability is evident from the descriptive statistics of bankrupt businesses, which are marked by low profitability, high leverage, limited liquidity, and ineffective asset use. Long-term financial difficulty is indicated by profitability measures with negative mean values (-0.08 and -0.09, respectively), such as Net Income to Total Assets (NI/TA) and Return on Assets (ROA). With significant standard deviations (38.13 and 22.89), the Return on Equity (ROE) and return on Capital

Employed (ROCE) exhibit sharp fluctuations, indicating that while some businesses can handle short-term gains, the majority face unpredictable financial performance. The too-high skewness and kurtosis numbers further support the idea that financial performance is extremely erratic across unsuccessful businesses.

The independent samples t-test results provided valuable insights into the differences in financial ratios between failed and non-failed companies. The analysis reveals that several financial ratios exhibit statistically significant differences, whereas others do not. Among the significant ratios, liquidity metrics such as the Current Ratio (CR) and Quick Ratio (QR) show p-values of 0.00098 and 0.00117, respectively, indicating that failed companies differ significantly in their ability to meet short-term obligations compared with non-failed ones.

15.2 Variable Selection Using PCA

In this study, PCA was used as a dimensionality reduction method to choose the most influential variables for predicting business failure from a set of 52 financial, macroeconomic, and non-financial variables. The primary goal of this feature selection approach was to eliminate redundant and less significant variables while retaining those that contributed the most to the variance in the dataset. Using principle Component Analysis, 28 relevant variables were discovered because of their significance.

The chi-square test applied to the PCA model produced a statistic of 5858.527, with 52 degrees of freedom (df) and a p-value of 0.000. Given that the p-value is extremely significant ($p < 0.05$), this suggests that the PCA model is effective in reducing data dimensionality and that the identified components account for a meaningful share of the variance within the dataset.

Table 1: Final selected variables for Prediction Model

Sr No.	Variables
1	**NI/TA** (Net Income to Total Assets)
2	**ROA** (Return on Assets)
3	**ROE** (Return on Equity)
4	**ROCE** (Return on Capital Employed)
5	**CR** (Current Ratio)
6	**QR** (Quick Ratio)
7	**D/E** (Debt to Equity Ratio)

8	**ICR** (Interest Coverage Ratio)
9	**ITR** (Inventory Turnover Ratio)
10	**ATO** (Assets Turnover Ratio)
11	**FAT** (Fixed Asset Turnover Ratio)
12	**CA/TA** (Current Assets to Total Assets)
13	**CF/D** (Cash Flow to Debt)
14	**TD/TA** (Total debt to Total assets)
15	**WC/TA** (Working capital to Total assets)
16	**RE/TA** (Retained Earnings to Total Assets)
17	**EBIT/TA** (EBIT to Total Assets)
18	**SL/TA** (Sales to total assets)
19	**PH** (Promoters Holdings)
20	**PUBH** (Public Holding)
21	**IIH** (Institutional investors)
22	**AGE** (Age of the company)
23	**INFL** (Inflation Rate)
24	**RIR** (Real Rate of Interest)
25	**CCI** (Consumer Confidence Index)
26	**BCI** (Business Confidence Index)
27	**GDP** (Gross domestic product)
28	**PMI** (Purchase Managers Index)

15.3 Regression Analysis

Logistic regression was applied to analyze the impact of financial, non-financial, and macroeconomic factors on business failure prediction. The dependent variable in the model represents financial distress, coded 1 for failed companies and 0 for Non-Failed companies. This study examined the following three models:

- Model 1 considers only financial ratios to predict business failure.
- Model 2 incorporates non-financial and macroeconomic variables.
- Model 3 incorporates financial, non-financial

It is essential to assess how well various predictive models fit the data to select the most robust and dependable model for business failure prediction. A statistical method called the Likelihood Ratio Test (LRT) compares nested models by examining the variations in their log-likelihood values. The prediction power of the three models created to evaluate the probability of business failure in Indian enterprises was compared in this

study using LRT. Finding the model that best fits the data is crucial because the models vary in terms of their variables and complexity.

Table 2: Comparison of Regression Model Fit

Comparison	χ^2 Statistic	p-Value	Interpretation
Model 1 vs. Model 2	802.28	0	Model 1 fits significantly better than Model 2
Model 1 vs. Model 3	-147.93	1	No significant difference between Model 1 and Model 3
Model 2 vs. Model 3	950.21	0	Model 3 fits significantly better than Model 2

Null Hypothesis (H_0): A simpler model fits the data as well as a more complex model.

Alternative Hypothesis (H_1): The more complex model provides a significantly better fit to the data.

Comparing Models 1 and 2, the LRT result ($\chi^2 = 802.28$, p-value = 0.0000) shows that Model 1 fits the data far better than Model 2 does. The null hypothesis (H_0) that both models fit equally well is rejected because the p-value is less than the cut-off value of 0.05. This implies that Model 1 predicts business failure more accurately than Model 2 does.

Model 1 versus Model 3: The LRT result indicates that there is no discernible difference between the two models ($\chi^2 = -147.93$, p-value = 1.0000). Model 3 has a marginally higher chance in a situation with a negative chi-square value, but we are unable to rule out H_0 because of the p-value of 1.0000. This suggests that the forecasting accuracies of the two models were comparable.

Model 2 against Model 3: Model 3 performs noticeably better than Model 2, according to the LRT results ($\chi^2 = 950.21$, p-value = 0.0000). The null hypothesis is rejected with a p-value of less than 0.05, suggesting that Model 3 offers a significantly superior fit for forecasting business failure.

15.4 Traditional Prediction Models Analysis

Table 3: Comparative performance analysis of Traditional Models

Model	Non-Failed Accuracy	Failed Accuracy
Altman Modified	1	0.9886
Ohlson	1	0.9742
Springate	1	1
Taffler	1	1
Zmijewski	0.9615	1
F-statistic	0.00079	
P-value	0.97822	

H_0: There is no significant difference in predictive accuracy among the existing business failure models.

H_1: There is a significant difference in predictive accuracy among the existing business failure models.

According to the findings of the repeated-measures ANOVA test, there was no discernible variation in the prediction accuracy of the business failure models ($F= 0.00079$, $p = 0.978$). Given that $p > 0.05$, we are unable to rule out the null hypothesis (H_0) and come to the conclusion that there is no discernible difference in the five models' predictive accuracy. This implies that all models predict business failures for both failed and non-failed enterprises with comparable accuracy. As a result, no model in this dataset exhibited a statistically superior prediction ability.

15.5 Analysis of Machine Learning Models

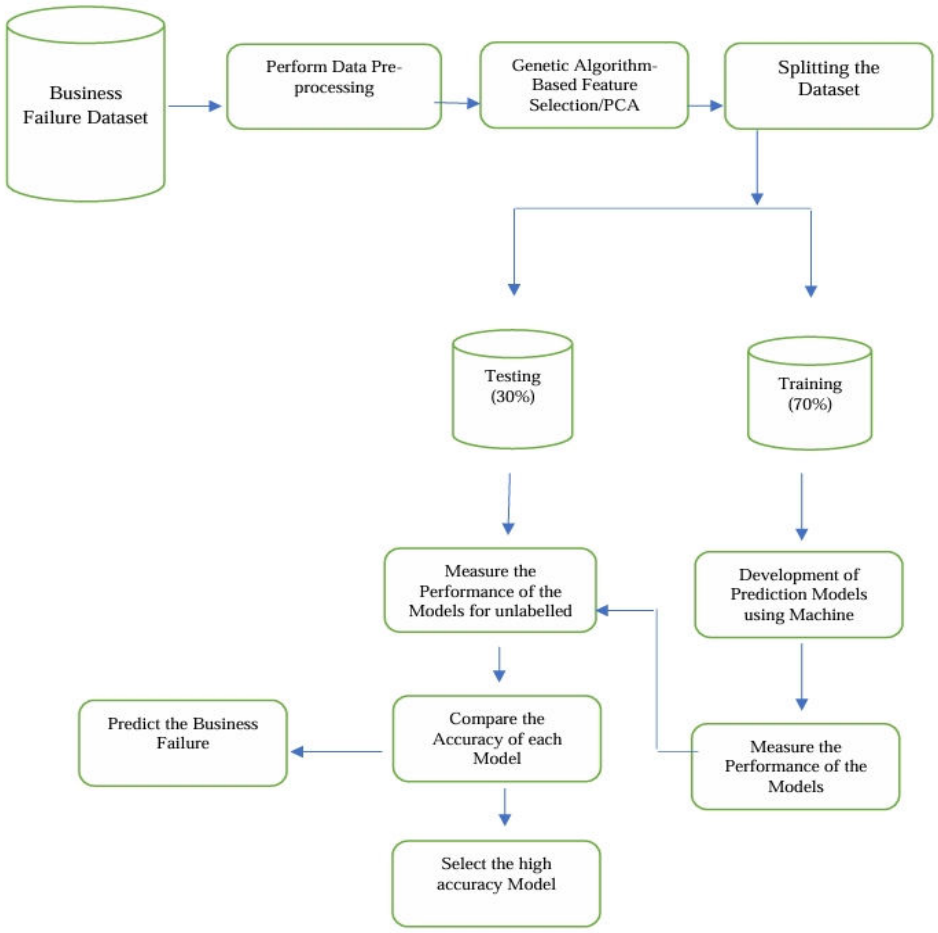
Business Failure Dataset
Perform Data Pre-processing
Genetic Algorithm-Based Feature Selection/PCA
Splitting the Dataset
Testing (30%)
Training (70%)
Measure the Performance of the Models for unlabelled
Development of Prediction Models using Machine
Predict the Business Failure
Compare the Accuracy of each Model
Measure the Performance of the Models
Select the high accuracy Model

Figure 1: Process of Developing Business Failure Prediction Model

Figure 2 shows six predictive models were tested: Random Forest, Support Vector Machine (SVM), Logistic Regression, Neural Network, Decision Tree, and Ensemble Methods. With an AUC-ROC of 1.0000 and a remarkable accuracy of 99.52%, the Random Forest model proved to be flawless in differentiating between failed and non-failed businesses. According to the confusion matrix, the model obtained high F1-Scores for both classes and incorrectly identified only one non-failed company as a failing company.

In contrast, the SVM model's accuracy of 76.67% and AUC-ROC of 0.8808 indicated a comparatively poor performance. According to the confusion matrix, lower precision and recall resulted from a higher misclassification rate, particularly for non-failed enterprises. Better results were obtained with Logistic Regression, which had an accuracy of 85.71% and AUC-ROC of 0.9210. With an F1-score of approximately 85.98% for the failed category, it showed balanced precision and recall values, suggesting a significant capacity to detect business failures accurately.

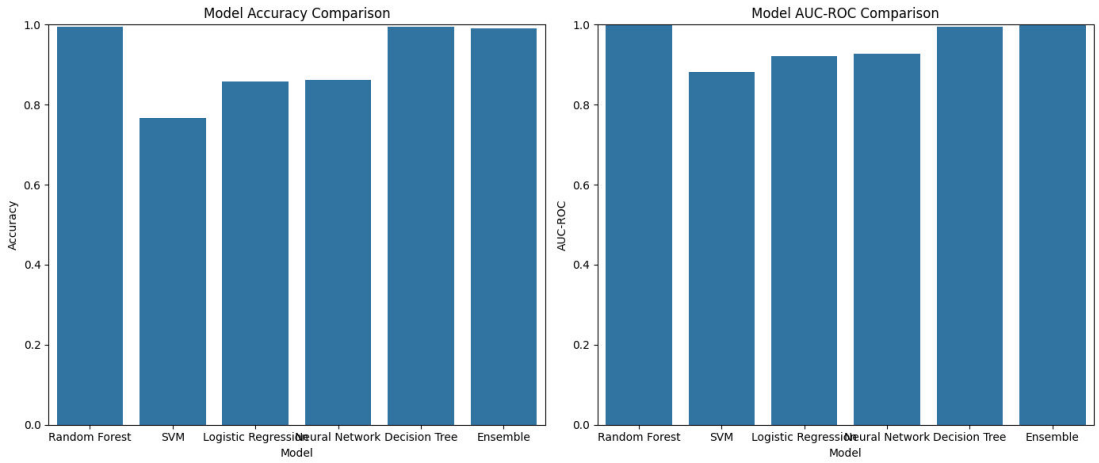

Figure 2: Model failed companies Testing Accuracy and AUC-ROC Comparison

Figure 3 with an accuracy of 96.19% and AUC-ROC of 0.9863, the Neural Network model significantly improved the results. Very few businesses were incorrectly classified in the confusion matrix, suggesting a high capacity for generalization over businesses that did not fail. The Ensemble Model was one of the most reliable classifiers, with 98.10% accuracy and an AUC-ROC of 0.9994. It maintained good precision, recall, and F1-scores while successfully reducing incorrect classifications.

Overall, the findings imply that when predicting both failed and non-failed businesses, tree-based models (Random Forest, Decision Tree, and Ensemble Methods) continuously outperform other models. On the other hand, logistic regression and neural networks produced findings that were reasonable but had somewhat higher rates of misclassification. The SVM model performed the worst, suggesting that it would not be able to handle business failure predictions with the dataset at hand.

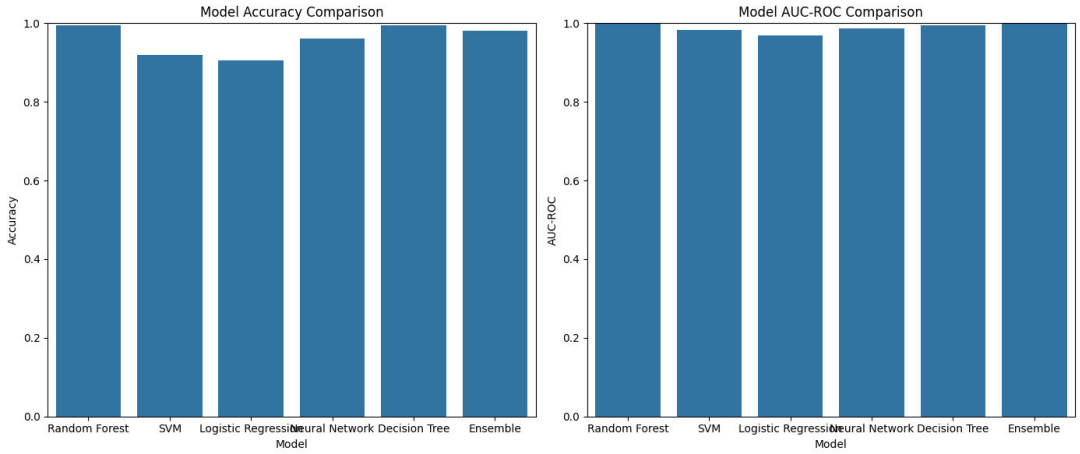

Figure 3: Model Non-failed co. Testing Accuracy and AUC-ROC Comparison

The Wilcoxon test was conducted to check the differences between paired sample testing accuracy of failed and non-failed companies, which are not normally distributed, which is often the case in machine learning model performance metrics. Unlike the t-test, this method does not assume normality.

Null Hypothesis (H_0): There is no significant difference between the testing accuracies of failed and non-failed companies.

Alternative Hypothesis (H_1): There is a significant difference between the testing accuracies of failed and non-failed companies.

The Testing of Accuracy Failed Companies group had higher values (Mdn = 0.99) than the testing accuracy of the Non-Failed companies' group (Mdn = 0.97). The Wilcoxon Test indicated that this difference was not statistically significant (W = 3, p = .465. The p-value of .465 is above the specified significance level of 0.05. Therefore, the result of the Wilcoxon test was not significant for the present data, and the null hypothesis was retained. Therefore, it was assumed that both the samples were from the same population. The effect size r is 0.3. When r = 0.3, there was a small effect.

15.6 Comparative Performance of Traditional and Machine Learning Models

Table 4: Comparative Accuracy performance of Traditional and Machine Learning Models

Traditional Models	Machine Learning Models
0.354	0.9952
0.565	0.919
0.241	0.9952
1	0.9619
0.967	0.981
0.986	0.9952
0.978	0.7667
0.093	0.9952
0.235	0.9905
0.071	0.9905

Traditional models have substantially lower accuracy than machine learning models. The median accuracy (Mdn) for Traditional Models was 0.46, whereas Machine Learning Models had a median accuracy of 0.99. This implies that Machine Learning

Models consistently outperform Traditional Models in terms of accuracy when predicting business failure.

The Mann-Whitney U test was used to determine whether the observed difference between the Traditional and Machine Learning Models was statistically significant. The U statistic is 20, with sample sizes of 10 for Traditional Models (n_1) and 10 for machine-learning models (n_2). The p-value was 0.023, which was less than the significance level of 0.05. The null hypothesis was rejected because the p-value was less than 0.05, indicating that there was a statistically significant difference in the prediction accuracy between the traditional and machine learning models.

15.7 Performance analysis of Machine Learning Models in Advance Time Horizon

Kruskal-Wallis test

Null Hypothesis (H_0): The predictive accuracy of Machine Learning models does not exhibit substantial variation when predicting business failure at 3-year, 2-year, and 1-year time horizons.

Alternative Hypothesis (H_1): The predictive accuracy of Machine Learning models exhibits substantial variation when predicting business failure at 3-year, 2-year, and 1-year time horizons.

Table 5: Performance Trends across Different Time Horizons (3 Years, 2 Years, and 1 Year) Prediction performance is best for shorter time horizons (1 year in advance), with a minor drop when the prediction window widens to 2 and 3 years. Random Forest and Ensemble Methods regularly outperform other models, with the greatest accuracy and AUC-ROC scores across all prediction intervals. Neural Networks and Decision Trees exhibit overfitting, with perfect training performance (100% accuracy and AUC-ROC) but reduced generalization during testing.

Table 5: Best Performing Models Across All Time Horizons

Model	3-Year Accuracy	2-Year Accuracy	1-Year Accuracy	Key Observations
Random Forest	91.07%	91.43%	88.21%	Best overall performer; highest stability over time.
Ensemble (Boosting)	88.93%	89.64%	87.14%	Strong generalization; reliable for risk prediction.
Logistic Regression	85.00%	86.79%	85.71%	Good for interpretability; consistent accuracy.
SVM	86.43%	87.50%	85.36%	Stable but slightly lower recall for failed firms.
Decision Tree	87.50%	88.93%	84.64%	Overfits training data; prone to minor accuracy drops.
Neural Network	84.64%	83.57%	83.93%	Overfitting: struggles with longer-term predictions.

The Kruskal-Wallis test showed a chi-squared (χ^2) value of 2.44, two degrees of freedom (df), and a p-value of 0.296. We cannot reject the null hypothesis (H_0) because the p-value is above the customary threshold of 0.05. This implies that there is no statistically significant difference in the model accuracy for predicting business failure over three, two, and one years. Median Accuracy Scores: The median forecast accuracy was fairly stable throughout the time horizons, with 3-year (86.97), 2-year (88.22), and 1-year (85.54) predictions exhibiting little difference. Mean Rank Comparison: The mean ranks of model accuracy over different time horizons vary slightly (9.92 for 3 years, 11.67 for 2 years, and 6.92 for 1 year), but the differences are not statistically significant.

16. Findings

The findings of this study make an important contribution to the growing body of research on business failure prediction, particularly in Indian enterprises. This study goes beyond previous models by including financial, non-financial, and macroeconomic aspects, providing a more comprehensive approach to failure prediction.

Disparities Between Non-Failed and Failed Companies' Financial Ratios

The financial ratios show considerable differences between the financial conditions of non-failed and failed companies. Compared with non-failed businesses, failed enterprises have lower liquidity positions, higher leverage, and negative profitability.

The average NI/TA for non-failed businesses is 0.090, but the average for failed businesses is -0.08, which denotes ongoing losses. The mean ROA for non-failed businesses is 0.10, whereas the mean ROA for failed businesses is -0.09, which further amplifies the profitability gap. Failed firms exhibit extreme volatility in ROE (mean = 1.13, standard deviation = 38.13), whereas non-failed firms maintain a stable and positive ROE (mean = 0.19). Non-failed companies have a higher ROCE (mean 0.21) than failed firms (mean 0.93), further highlighting the inefficiencies in capital utilization by failed companies

Validation of Traditional Models in an Indian Context

The study evaluated the ability of established models, such as Altman's Z-score, Ohlson's O-score, Springate, Taffler, and Zmijewski, to predict business failure among Indian enterprises. The results show various levels of predicted accuracy, demonstrating the models' strengths and limits in emerging countries. This study demonstrates that while these models provide a baseline assessment, they may need to be modified to properly reflect India's unique economic structure. These models did not perform as expected in predicting business failures based on their accuracy.

Machine Learning vs. Traditional Models

A significant addition is the comparison of classical models with machine learning models, such as Random Forest, SVM, Logistic Regression, Neural Networks, Decision Trees, and Ensemble Methods. The findings show that machine learning models routinely outperform traditional models in accuracy and predictive capacity, highlighting the value of modern computational techniques in financial risk assessment. The above-mentioned prediction models, the random forest, decision tree, and ensemble models, performed well in predicting the failure accuracy.

Time Horizon Analysis and Predictive Consistency

The study examined model performance over three time horizons, demonstrating that forecast accuracy often improves as a failure event approaches. This conclusion reinforces the dynamic character of financial hardship, underlining the importance of early warning mechanisms in business risk-management methods.

Statistical Validation of Model Accuracy

The study uses statistical tests such as descriptive statistics, correlation analysis, PCA, Regression, t-test, Likelihood Ratio Test (LRT), and the Kruskal-Wallis test to prove strong empirical evidence that some models perform much better than others. This supports the use of data-driven and adaptable models for failure prediction rather than traditional financial ratio-based strategies.

17. Recommendations and Directions for Future Research

Businesses can improve financial stability by improving liquidity management, diversifying revenue streams, and using machine learning models for early warnings. Maintaining a positive Working Capital to Total Assets ratio ensures short-term solvency, whereas strengthening profitability margins reduces earnings volatility and protects against financial shocks. Investors can use predictive models to assess firm viability, whereas banks can use machine learning to assess credit risk.

Traditional models such as Altman's Z-score and Ohlson's O-score may be refined for emerging markets by adapting to India's unique economic structure and regulatory environment.

Advancements in machine learning techniques, including deep learning applications such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for enhanced predictive accuracy and hybrid models combining machine learning with traditional statistical methods, can be developed.

Incorporating a broader range of macroeconomic indicators, specific sectors, and non-financial factors such as corporate governance, market sentiment, and environmental sustainability metrics may be included for model completeness. A Study of the impact of regulatory changes on business survival rates and failure prediction can be undertaken.

The dynamic and ever-changing nature of financial crises requires ongoing improvements in predictive modeling. Although this study establishes a core framework for predicting business failure, many areas for future research remain unexplored.

18. Conclusion

This study evaluates the effectiveness of traditional failure prediction models, such as Altman's Z-score, Ohlson's O-score, Springate, Taffler, and Zmijewski, in Indian corporate failures. These models are often constrained by rigid linear assumptions and their limited adaptability to modern financial environments. This study also advances predictive analytics with machine learning, benchmarking the performance of Random Forest, Gradient Boosting, SVM, Decision Trees, and Neural Networks. Ensemble-based algorithms outperform traditional models in terms of accuracy and robustness and capture deeper financial distress signals. The study also found that predictive reliability marginally improved as failure progressed, but the statistical differences remained insignificant. These findings serve as a blueprint for AI-driven financial surveillance systems, advocating automated, real-time financial distress monitoring to mitigate systemic risks.

19. Chapter Scheme

This thesis is structured into five chapters, presented in logical sequence, to guide the reader throughout the research process.

Chapter 1: Introduction: This chapter sets the stage for this study by providing background information on business failure prediction and highlighting its significance in India. It establishes the research problem, formulates the research questions and objectives, and outlines the potential contributions and limitations of this study. This chapter provides a clear and concise overview of the research, motivating the need for the study and outlining its scope and objectives.

Chapter 2: Conceptual Background and Literature Review: This chapter delves into the theoretical underpinnings of business failure prediction and reviews the existing literature on relevant concepts, models, and empirical findings. It critically examines previous research on financial distress, bankruptcy, and corporate failure and identifies key factors and methodologies used in predicting business failure. This chapter provides a comprehensive overview of the existing body of knowledge, identifies research gaps, and establishes a theoretical foundation for this study.

Chapter 3: Research Design and Methodology: This chapter details the methodological approach employed in this study. It describes the data sources, sample selection criteria, variable definitions, and the statistical techniques used for data analysis. This chapter provides a transparent and detailed account of the research design to ensure the replicability and validity of the study's findings.

Chapter 4: Data Analysis and Interpretation: This chapter presents the results of the data analysis and interprets the findings according to the research questions and objectives. It provides a comprehensive analysis of the financial and nonfinancial factors contributing to business failure in Indian companies and evaluates the predictive accuracy of the proposed model. This chapter provides a clear and concise presentation of the research findings and supports the conclusions.

Chapter 5: Findings, Recommendations and Conclusion: This chapter summarizes the key findings of the study, draws conclusions, and offers practical suggestions for stakeholders. It discusses the implications of the research for company management, lenders, investors, and policymakers and provides recommendations for mitigating business failure risk and promoting financial stability in the Indian business environment. This chapter aims to synthesize research findings and provide actionable insights and recommendations for practical applications.

This structured approach ensures a coherent and logical flow of information, guiding the reader through the research process, from problem identification to conclusions and recommendations.

20. References

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21. Papers published

1. D'Souza, A., & R, C. (2024). Impact of macroeconomic factors on business failure: an empirical study of Indian companies. ShodhKosh: Journal of Visual and Performing Arts, 5(6), 2123–2130. https://doi.org/10.29121/shodhkosh.v5.i6.2024.2918)
2. Souza, A. D., & R, C. (2023). Application of Altman's Z-score model in predicting business failures of selective hospitality companies in India. BOHR International Journal of Finance and Market Research, 2(1), 44–49. https://doi.org/10.54646/bijfmr.2023.20
3. D'Souza, A., Chandrashekhar, R., & Jagadisha. (2023, January 27). Non-Performing assets of co-operative societies in Dakshina Kannada – a case study. https://journals.ijramt.com/index.php/ijramt/article/view/2517

Papers presented

1. Presented a paper in Drishti-2024, International Conference organized by Vivekananda College of Engineering and Technology, Puttur on a topic "Determinants of Small and Medium Enterprise Failure in India: A Financial and Operational Perspective" on 11th September 2024.
2. Presented a paper on the topic "Macroeconomic Variables Indicating Business Failure- an Empirical Study on Indian Companies" at International Conference on Technology, Innovation and Entrepreneurship for Sustainable Global Development & Economic Growth (ICTIEE'2024) Organized by Apeejay Institute of Management & Engineering Technical Campus, Jalandhar on April 6th 2024.
3. Presented a paper at the International conference Drishti-2023 on the topic Macroeconomic factors leading to Business Failure: A study on Indian Companies organized by Vivekananda College of Engineering and Technology Puttur on 26th July 2023.
4. Presented on "Business Failure Prediction: A Study of Selected Indian Companies using Altman Z score Model" is presented in the National Conference on Advances in Science, Technology and Management held at Vivekananda College of Engineering & Technology, Puttur on 23rd and 24th August 2019.
5. Presented paper on Financial Innovation & its Impact in International conference on "Multi-Disciplinary business research - the new drivers of business innovation" on 31st March 2017, at AIMIT at Mangalore.

22. Workshops attended

1. Attended a one-day symposium on "Incubation Facilities and Startups: Creating Impact in the Startup Ecosystem," organized by the Kanara Chamber of Commerce and Industry in Mangalore on 9th December 2023.
2. Participated in a three-day Faculty Development Programme (FDP) on "Intellectual Property Rights (IPR) and IP Management," conducted by IFERP, Chennai, virtually from 26th to 28th April 2023.
3. Participated in a webinar on "Challenges and Opportunities in Higher Education Abroad," organized by IFERP, Chennai, virtually on 15th March 2023.
4. Workshop on "Data-Driven Insights for Managerial Decision-Making," conducted by IFERP, Chennai, on 20th February 2023.
5. Participated in an online FDP on "Advanced AI and Data Analytics with Implementation Techniques," organized by IFERP, Chennai, from 12th to 16th December 2022.
6. Participated in a webinar on "Cyber Security with Ethical Hacking," conducted by the Institute for Engineering Research & Publication in Chennai, on 30th November 2022.
7. Completed a Professional Development program, approved by IGNOU and UGC, held in Delhi from 21st to 29th September 2022.
8. Participated in the webinar "Discover Emerald journals for your academic excellence and research". On 13th December 2021.
9. Participated in online user awareness session jointly organized by VTU Consortium and Springer Nature on 13th Dec '2021.
10. National Level Webinar on Investor Awareness Program conducted by Mangalore University in association with Ambition Learning Solutions held on 02nd August, 2021.
11. Completed the module 10 reasons to get – and use – an ORCID iD on Wednesday 16 June, 2021 ELSEVIER research academy.
12. Completed the module Plagiarism: Decision making & dealing with grey-zones across academic Fields on Wednesday 27 January, 2021 from ELSEVIER research academy.

13. Successfully completed the module the journal publishing cycle on Tuesday 22 June, 2021 from ELSEVIER research academy.
14. Completed the module Conference skills for researchers on Monday 25 January, 2021 from ELSEVIER research academy.
15. A two-day online workshop on "Aligning yourself to the publishing process on 23rd and 24th July 2020, organized by ELSEVIER, South Asia.
16. 5-day online workshop on "Application of Econometrics in Business Research" Christ Deemed to be University from 23rd-27th June 2020.
17. Webinar on Learning in the Digital Age- Age-Opportunities and Challenges, organized by Govinda Dasa College on 20th June 2020.
18. Participated in a workshop on Emerging Perspectives in Commerce, Management, and Research Methodology held at Vivekananda College of Engineering & Technology, Puttur, on the 17th and 18th of October 2019.
19. VTU one-day training programme on E-Resources for Academic Excellence, on 21st September 2019 at Vivekananda College of Engineering & Technology.
20. Three days FDP on Holistic Pedagogy held at Vivekananda College of Engineering & Technology on 23rd to 25th July, 2018.
21. Workshop on Research Methodology held at University College, Mangaluru on 28th July 2019.
22. Participated in a one-day workshop on research Methodology at Mangalore University on 30th April 2018
23. Workshop on Research Methodologies & Latex held at Vivekananda College of Engineering & Technology, Puttur from 21st to 23rd September 2017, Puttur.
24. Workshop on Advanced Excel held at Mangalore University from 29th April to 1st May 2017.